Investigative case studies: Metrics design, logic, adding value

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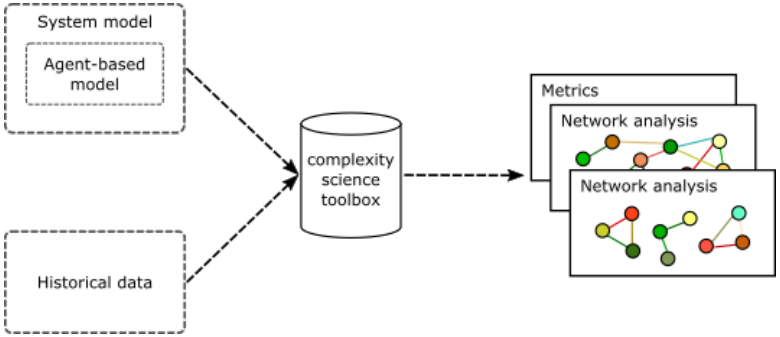
WP5 objectives

- Identification of metrics of the networks describing the interaction between the different elements in the model.
- Analyse the results of the investigative and adaptive case studies



Tasks status

Task 5.1: Metrics definition (M2-M11) UniBo ✓

Task 5.2: Investigative case studies analysis (M7-M16) UniBo

Task 5.3: Adaptive case studies analysis (M17-M22) UniBo

Overview of presentation

- **Classical** metrics: delays, costs, etc.
  - In **mean**: average values
  - In **tail**: *quantiles* of distributions
  - **standard** network metrics

- **Non-classical** network metrics
  - **centrality**
  - **causality**

Classical metrics

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Standard ATM metrics

Definition

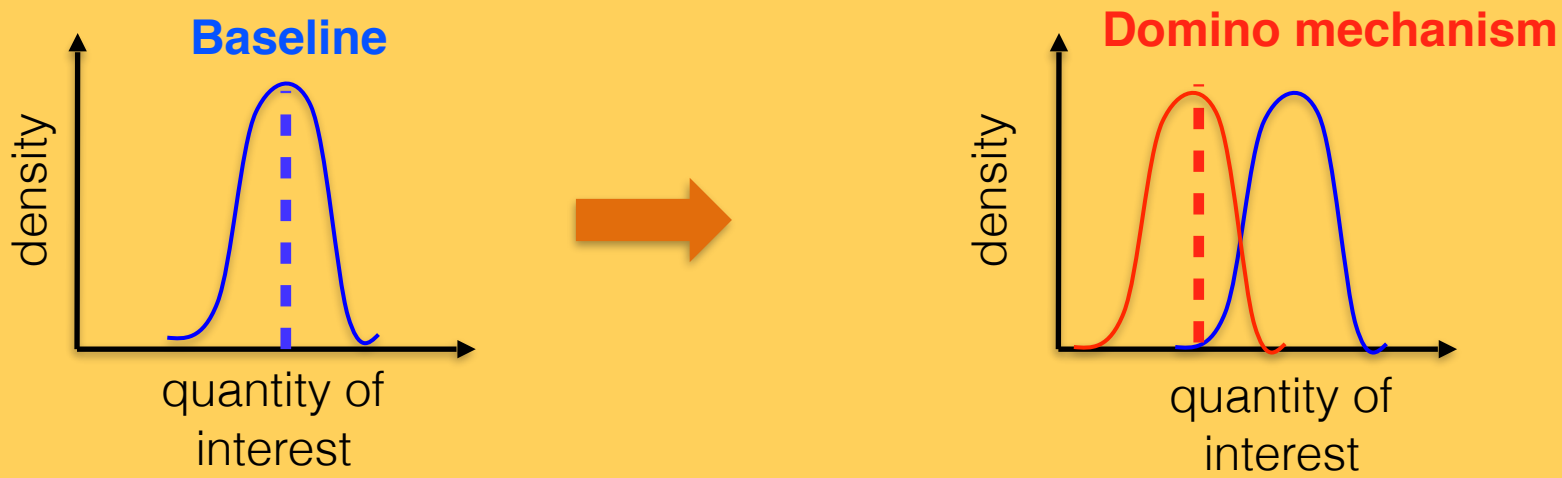
- **Delay**:
  - departure, arrival, and gate-to-gate *delay*
  - delays weighted with the number of *passengers* per flight
  - percentage of flights with delays larger than a given *threshold*
  - *total* delays
  - missed *connections*
  - departing (arrival) queue delay at airports
- **Cost**:
  - excess costs of *fuel*
  - *passenger* costs: compensation, duty of care, cost of rebooking, soft costs
  - *non-passenger* costs: crew and maintenance
  - *percentage* of flights incurring different types of costs
  - *total* excess cost (M3-M1)

Standard ATM metrics 2

MEAN

How the averages change moving from the baseline to a scenario with some implemented mechanism

From time to time, it is crucial to select the subset of flights that is of interest for the analysis: regulated flights (e.g. UDPP), flights landing at airports with implemented E-AMAN, and so on



ATM metrics in Domino

- Standard ATM metrics address `means', but distributions might be important
- Standard ATM metrics ignore the network aspects

Our approach in Domino

More focus on the extreme (tail) events for standard ATM metrics

New metrics scaled up to the network level

New approach in Domino

More focus on the extreme (tail) events for standard ATM metrics

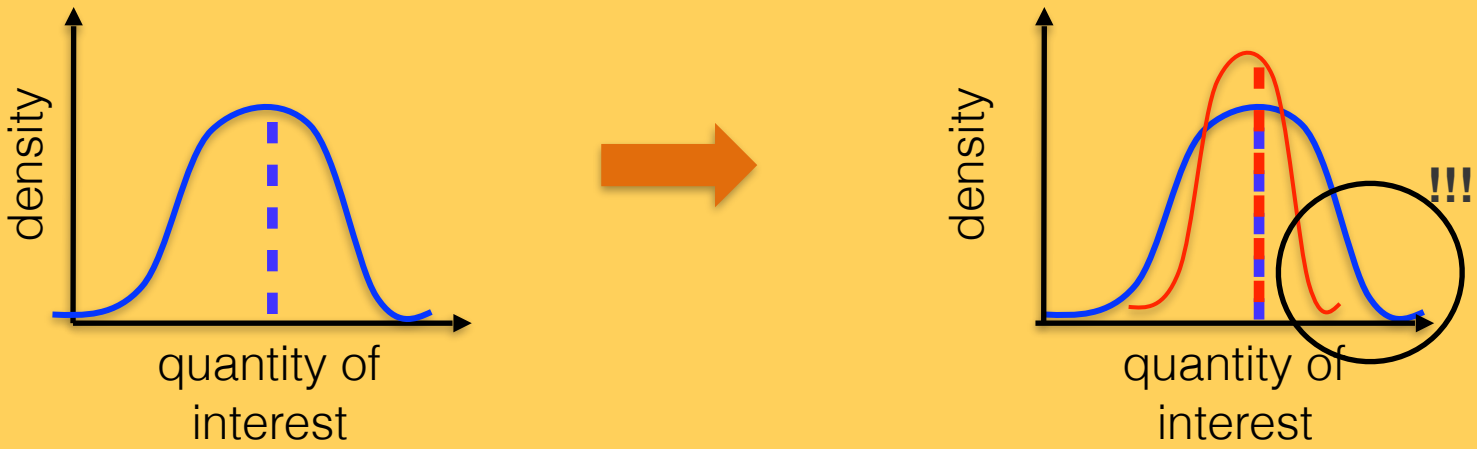
New metrics scaled up to the network level

Extreme events

TAIL

Sometimes, it is more important focusing on *extreme events*

We can have two distributions of delays, e.g., with similar means but describing different kinds of extreme events:
—> we have to look at the *tail* of distributions



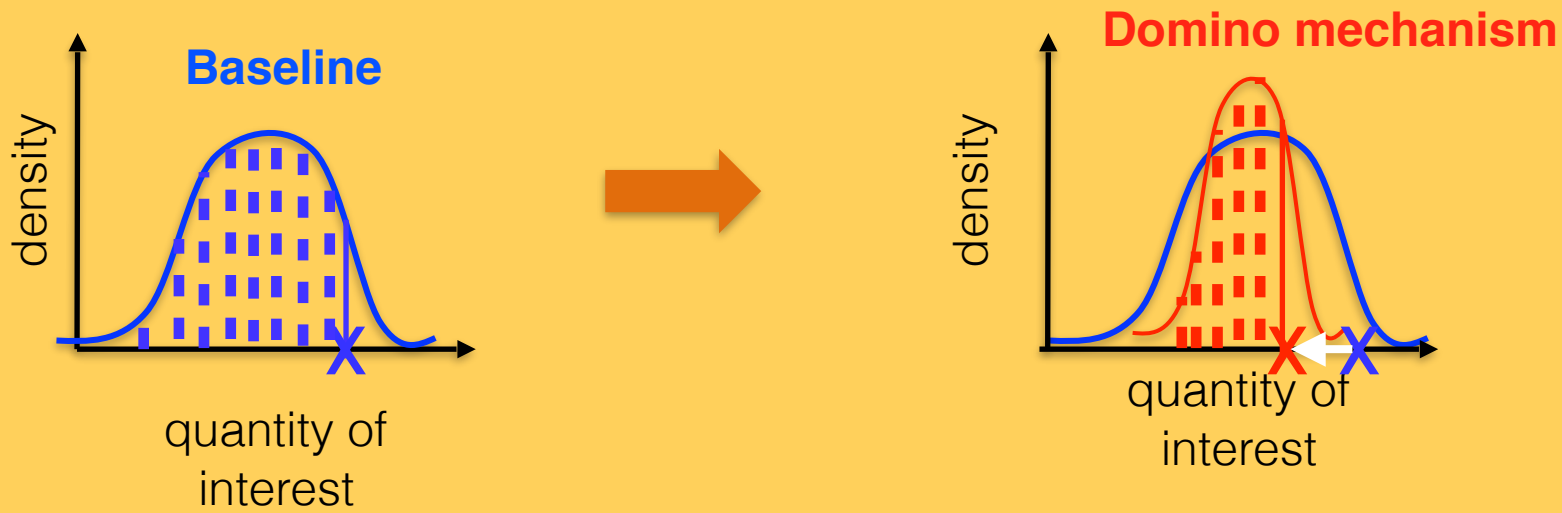
Extreme events: quantiles

TAIL

How to characterise extreme events looking at the distributions?

α **-quantile** is the cut point dividing the distribution in two ranges containing α observations on the left and $1-\alpha$ on the right

For instance, when moving from the baseline to a scenario with Domino mechanism, a decrease of the 90%-quantile for the delay distribution, e.g., means less occurrence of extreme delays



New approach in Domino

More focus on the extreme (tail) events for standard ATM metrics

New metrics scaled up to the network level

ATM network metrics

- Air traffic is naturally described as a network
- In Domino, we aim to assess and quantify the impact of innovations in a certain scenario at the *global level* from the result of the ABM

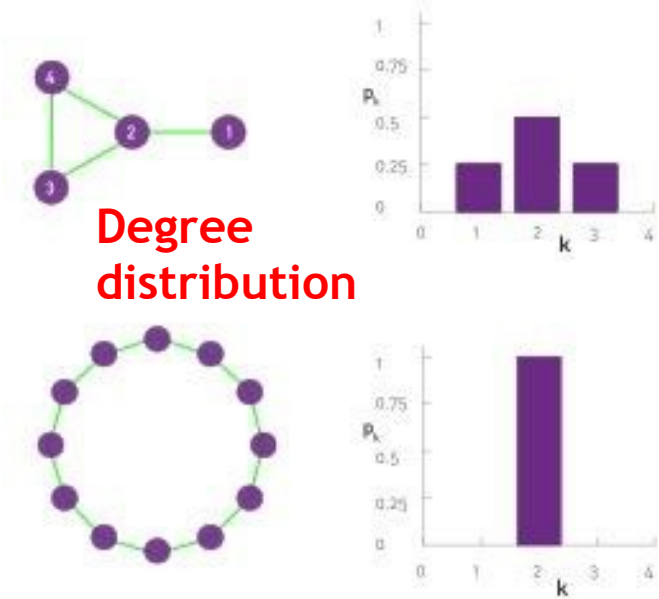
→ Network science provides us with tools to study the importance of the ATM subsystems, the interactions of network elements, the role of topology in the propagation of signals (e.g. delays or congestions) and in the network functioning

However, we need to generalise the standard network metrics or to define new network metrics which are better suited to our objectives.

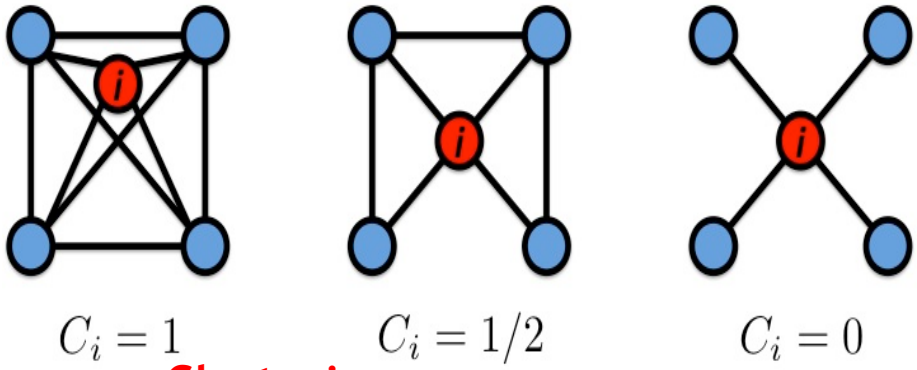
Standard network metrics

Centrality measures

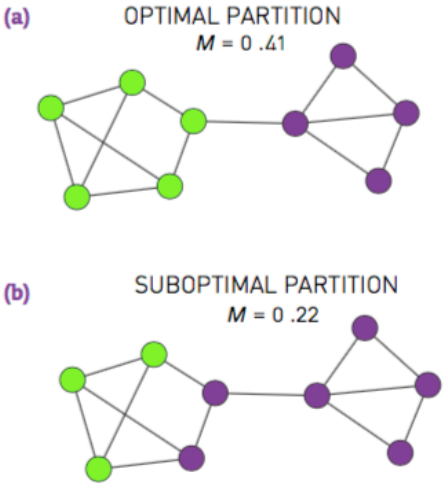
Figure 1.1: 15th Century Florentine Marriges Data from Padgett and Ansell [493]



Degree distribution



Clustering measures

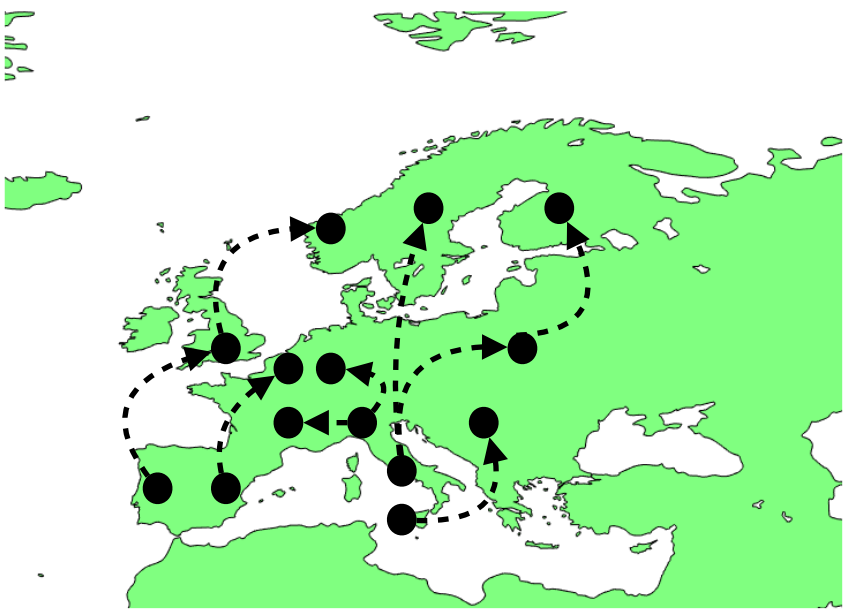


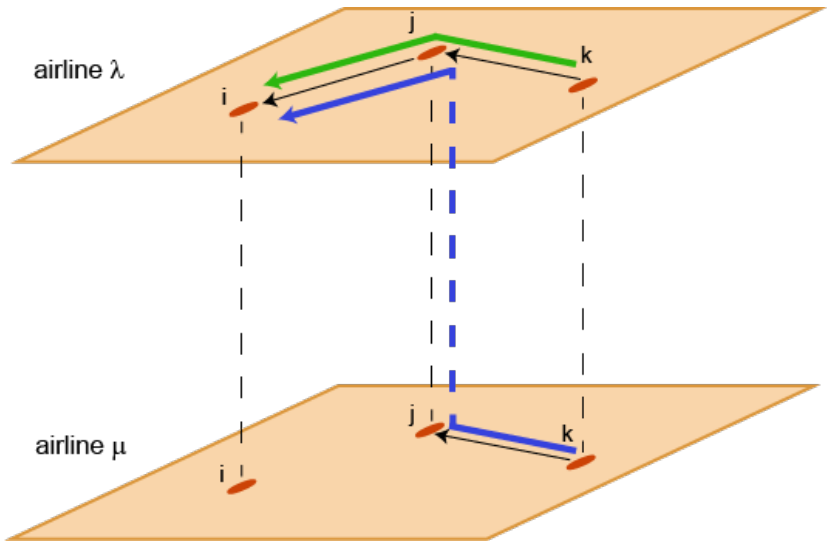
Modularity and communities

Characteristics of the ATM network

The ATM system can be naturally described as a network of nodes, i.e. subparts of the system such as airports, E-AMAN, NM, etc., and links connecting the nodes, i.e. flights or other `interactions' between subparts.
The ATM system can have also a multi-layers structure when considering each airline as a layer in the network of airports and flights.

It is a **temporal** (i.e. evolving in time), **multilayer** (i.e. different interacting agents, e.g. airlines) **directed network** with **non-zero travel time** (i.e. flight time).





ATM network metrics

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→ Network science provides us with tools to study the importance of the ATM subsystems, the interactions of network elements, the role of topology in the propagation of signals (e.g. delays or congestions) and in the network functioning

We need to generalise the standard network metrics or to define new network metrics which are better suited to our objectives.

Non-classical network metrics

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New ATM network metrics in Domino

Centrality metrics

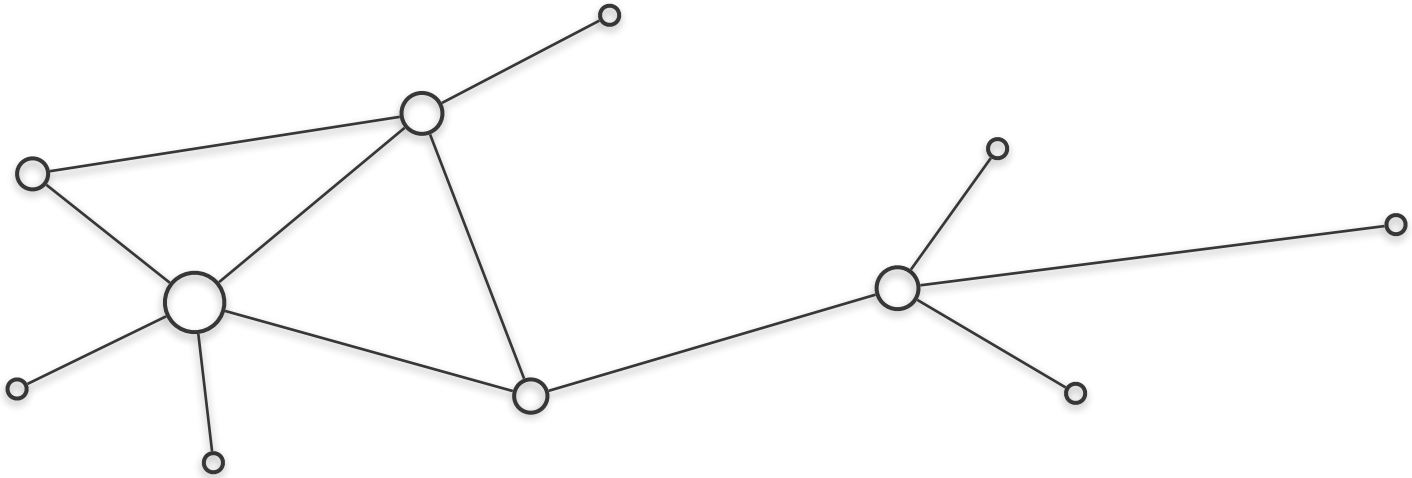
Causality metrics

Centrality metrics

Classical network metrics: centrality, degree distribution, betweenness, etc.

- Centrality metrics measure the importance of the network's nodes based on their connectivity, i.e. the potential to move through the network passing from that node
- If suitably defined, centrality can be used to assess the preservation of possible passengers' itineraries in the actual network
- Existing centrality metrics are not sufficient, as they do not consider the effect of delays on connectivity
- Need to introduce new centrality metrics

Centrality



Finding the most important nodes

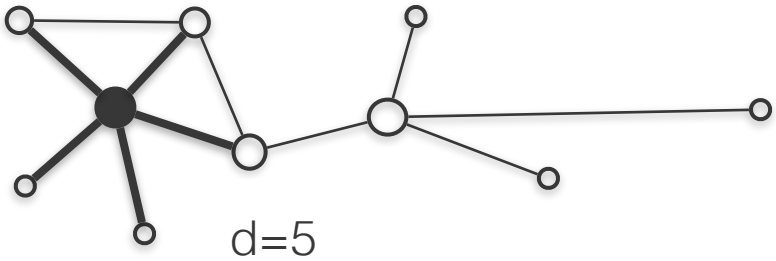
- ranking to identify key nodes (e.g., most important airports for connecting flights)
- spreading of `information' (e.g. delays, costs)
- travelling of passengers

Centrality metrics quantify a node's importance

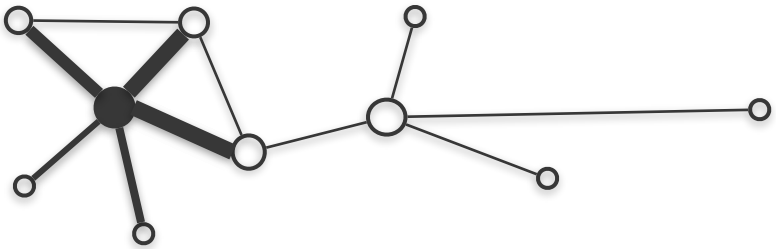
Several definitions of importance -> several centrality metrics

Centrality metrics

Degree and strength

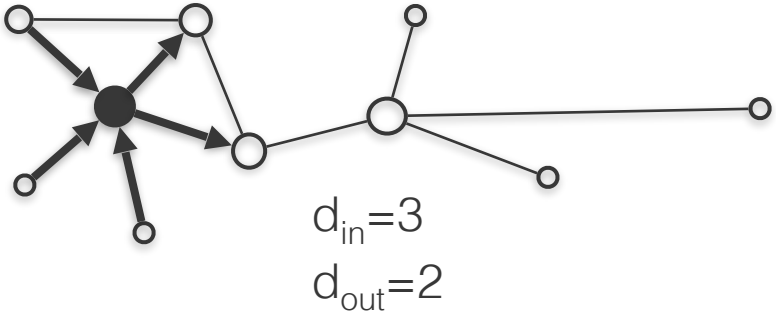


Weighted or multilink network



strength= sum of links' weights

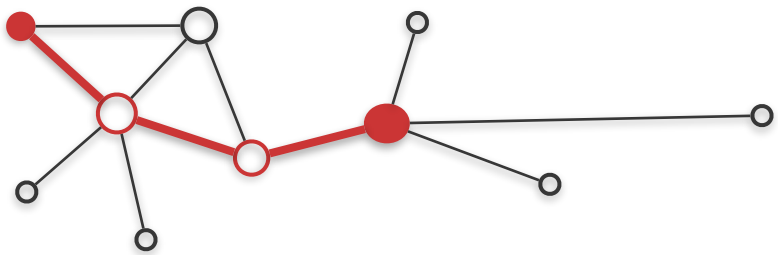
Directed network



Local role of the node

Centrality metrics

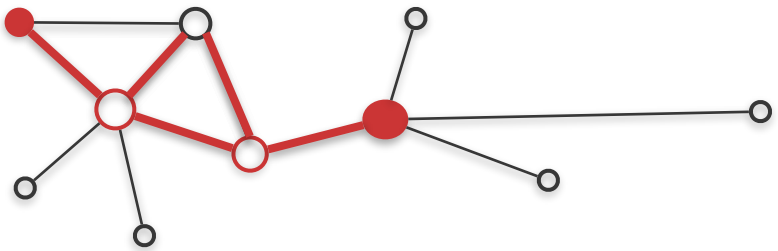
Based on shortest paths and distances



Betweenness centrality

$$b_i = \sum_{j,k \neq i} \frac{\#\ shortest\ paths\ between\ j\ and\ k\ passing\ from\ i}{\#\ shortest\ paths\ between\ j\ and\ k}$$

Based on walks



Katz centrality

PageRank

- Processes do not only proceed using shortest paths (like in ATM)
- Computed fast with matrix algebra

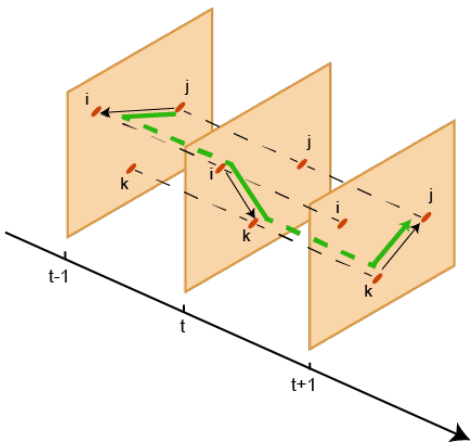
Definition of centrality based on walks

Outgoing (incoming) Centrality: number of walks leaving (entering) a node, but weighted with the length of the walk

Centrality for the ATM system?

with a focus on the network of airports&flights

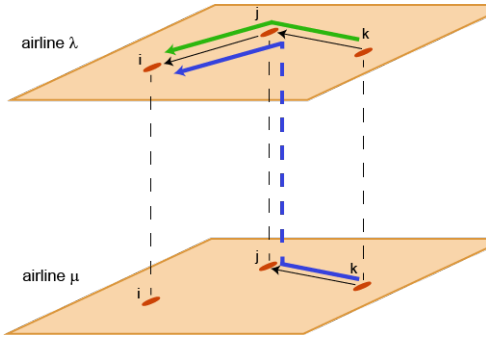
- **Walk** based centrality
  In ATM words, a walk can be a *passenger itinerary* (1-leg, 2-legs, and so on) or any possible *trip*
  - **Trip centrality** (considering any possible trip)
  - **Passengers' centrality** (considering only scheduled passengers' itineraries)



which accounts for ATM specific characteristics:

- **Temporal** structure (i.e. flights at the day of operation)
  Walks must be correctly time-ordered

- **Multilayer** structure (i.e. interactions among airlines)
  Walks can be intra- or inter-layer, but inter-layer walks might have less probability to be used (e.g. because the imply a *cost*), therefore should be weighted less



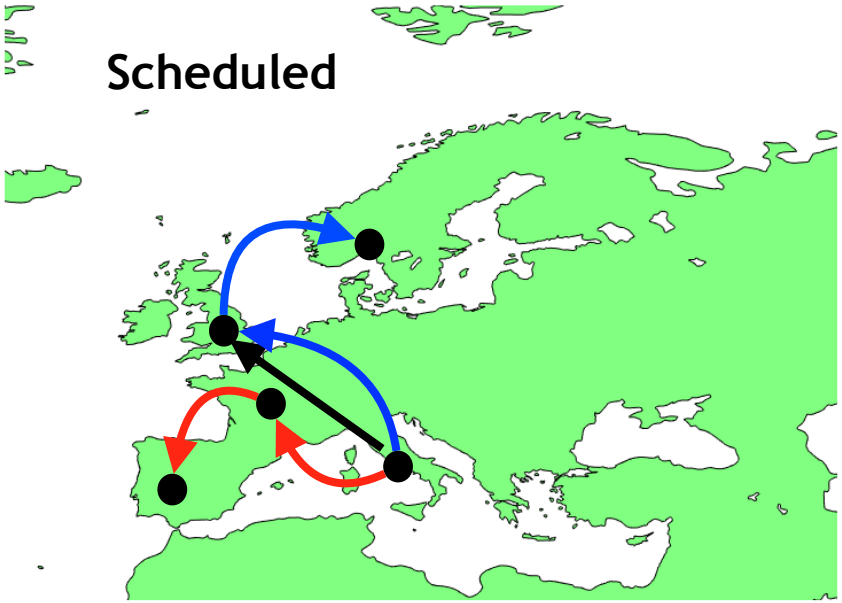
- **Non-zero travel** time (as any transportation system)
  (technical aspect: introduction of *secondary nodes* describing flights with given departure and arrival times)

How to use centrality metrics from an operative p.o.w?

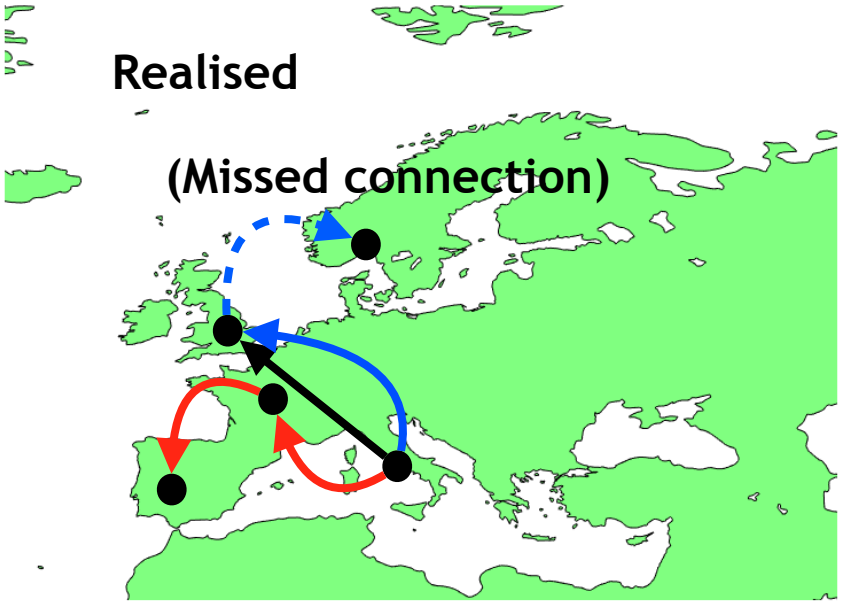
- We observe the **scheduled** network (M0 files) and the **realised** one (M3 files)
  - Network of realised flights differs from schedule due to delays and cancellations
  - Delays can disrupt connections, but the entity of their effect on an airport's connectivity depend in a complex way from the schedule
  - The **loss** of centrality quantifies this effect
  - *The smaller the loss is, the better that subsystem works*
  - How much does centrality change with implemented Domino mechanisms? —> we can quantify the improvement for each subsystem!

An example of passengers' centrality loss

Let us assume to consider three passengers's itineraries:
N passengers FCO -> LHR (**black**)
M passengers FCO -> LHR -> OSL (**blue**)
L passengers FCO -> CDG -> MAD (**red**)



Centrality FCO = N+M+L



Centrality FCO = N+L

- Passengers' centrality loss (=M) quantifies the disruption of connections in terms of the number of passengers per disrupted itinerary
- (Trip centrality loss quantifies the disruption of connections in terms of possible trips but weighted with the number of flights for each trip)

New ATM network metrics in Domino

Centrality metrics

Causality metrics

Causality metrics

Introducing more dynamic metrics, e.g. Granger causality, to study how the evolving ATM subsystems interact each other as times goes on.

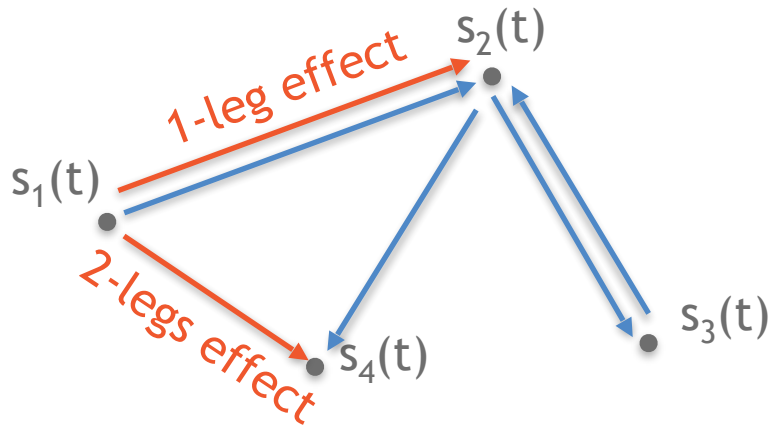
- The interaction of the system's elements fosters the transmission of signals on the network, like e.g. delays or congestions
- These interactions create causality relations between the system's elements
- Detecting causality relations, we can assess the interdependence among the system's elements
- Granger causality is a method to detect causality relations, but improvements needed to be implemented for application to Domino

How to build the network of `interactions'?

Causality relations

- Let us focus on the network of airports and flights (although the method is more general).

- Each airport is characterized by its "state of delay", the average departure delay of its flights (suitably detrended for daily seasonality)
- Does $s_2(t)$ influence $s_1(t)$? (is there a causal relation?)



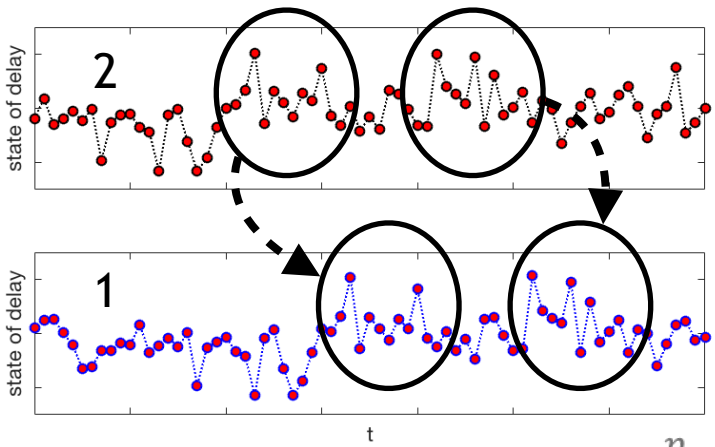
- A causal relation between two airports could arise, e.g., when they are connected by direct flights because of reactionary delays (1-leg effect) but also when they are not connected directly (2- or more-legs effect)

- **Once pairwise causal relations are detected, we can build a second network where links are the causal relations**
- Characterizing this network informs us on the delay propagation patterns

How do we detect causal relations?

Causality

Granger causality in mean



- Granger causality: a time series "2" `Granger causes' another time series "1" if the past history of "2" improves the prediction of the future of "1" when the past of "2" is taken into consideration
- Well established statistical test to detect causality between time series [Granger (1969)]

$$s_1(t) = \varphi_0^1 + \sum_{j=1}^{p} \varphi_j^{11} s_1(t-j) + \sum_{j=1}^{p} \varphi_j^{12} s_2(t-j) + \epsilon_t^1$$

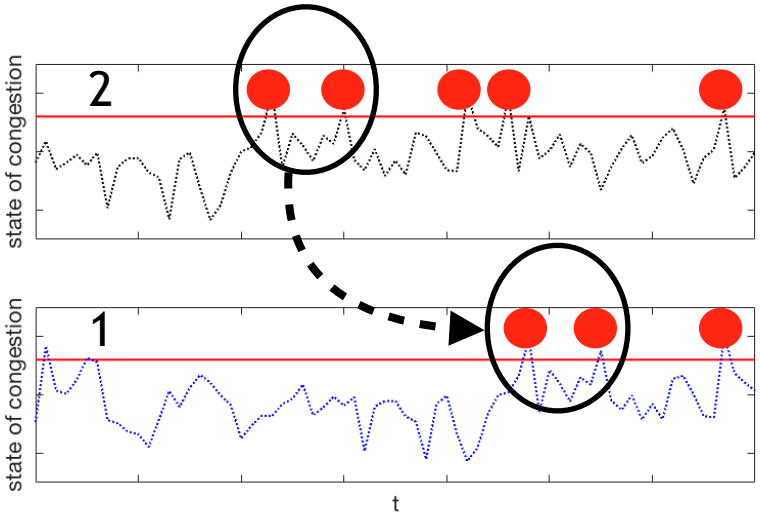
- Test null hypothesis that the φ_j^{12} are null
- If rejected, there is a causal relation between $s_2(t)$ and $s_1(t)$

- Every possible couple of airports is tested, and a "causality network" is built with the resulting links [Zanin et al. (2017)]

Causality metrics quantify the interactions of the system's elements

Causality for extreme events

Granger causality in tail



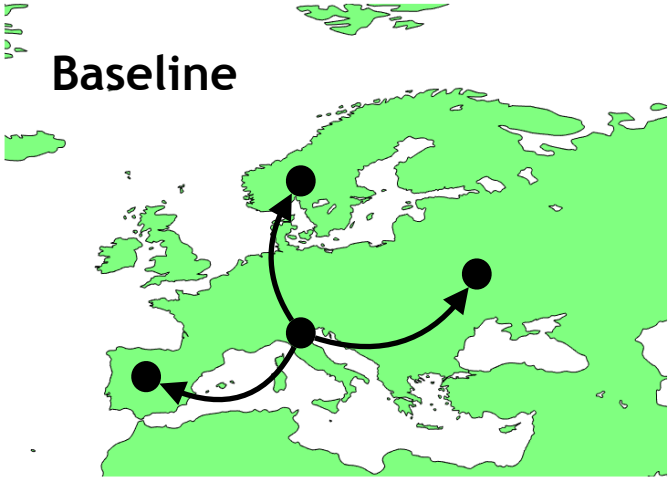
- `GC in mean' assumes linear dependence and weights equally small and `extreme' events
- Let us focus on the tail events, i.e. a time series of binary states:
  - 1, if the event is on the tail (i.e. above a given quantile)
  - 0, otherwise
- Granger causality in tail: a test for causality ("2" helps to predict "1"), but considering only if an event is extreme or not! [Hong et al. (2009)]

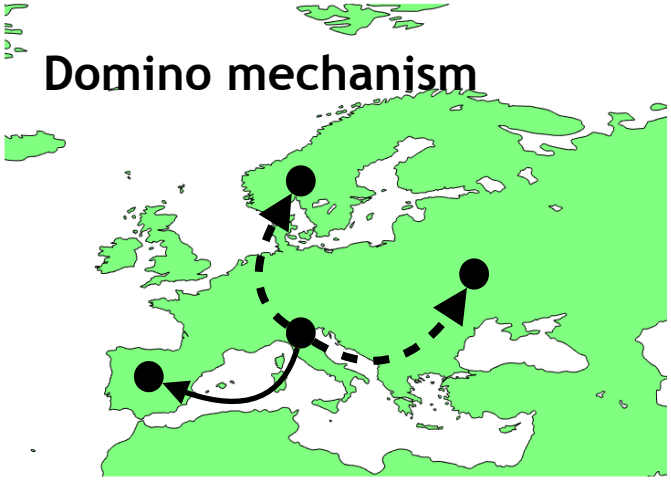
What time series?

- The **state of delay** of a node-airport, e.g. average delays of flights per hour
- The **state of congestion**, i.e. when the state of delay is `extreme'
- The **state of cost of delay**, e.g. to study how costs, and not delays, propagate throughout the system
- … and so on (the method is very general)

How to use causality metrics from an operative p.o.w?

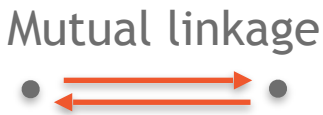
- **less causal links is better**
  a decrease of the node degree would represent an improvement!

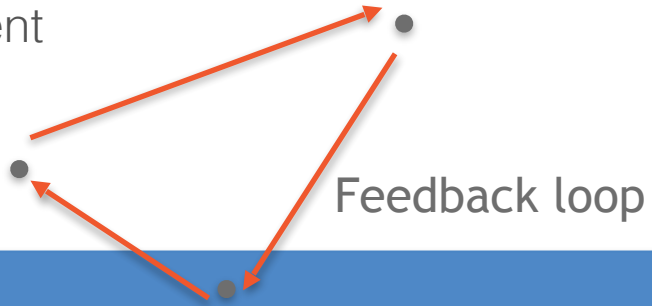




- Overespression of feedback loops and mutual linkages in the GC network (w.r.t. the random case) —> enhancing delay propagation

the decrease of these patterns due to innovations would represent an improvement





Thank you!

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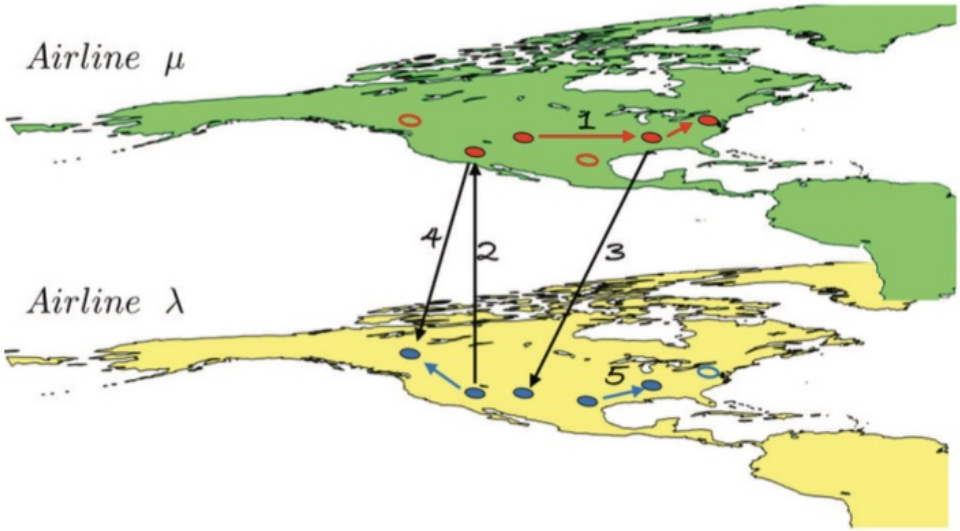
Multilayer Causality network (layer = airline)

- When diversified per airline, the causality network has a multi-layer structure.
  - The multi-layer causality network can be adopted to characterise how different airlines interact each other and to quantify the level of interaction.



- **Interaction 1**: delay propagation within the same airline (intra-layer links)
- **Interaction 2**: local causality relation between two airlines at the same airport
- **Interaction 3**: when airline μ 'Granger-causes' delays to airline λ at some airport served by both companies (one-leg effects)
- **Interaction 4**: when airline μ 'Granger-causes' delays to airline λ at some airport which is not served by μ (two or more-legs effects)